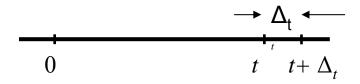
Postulates for a Poisson Process

- 1. Events in non-overlapping time intervals are independent.
- 2. For "small" Δ_t :
 - a) Pr [1 arrival in Δ_t] $\approx \lambda \Delta_t$
 - b) Pr [more than 1 arrival in Δ_t] ≈ 0
 - c) Pr [no arrivals in Δ_t] $\approx 1-\lambda\Delta_t$



Poisson Process

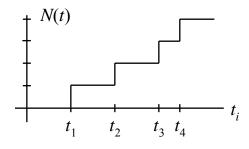
Arrivals:

Let $N(t_1, t_2)$ be the number of arrivals in the interval $[t_1, t_2)$

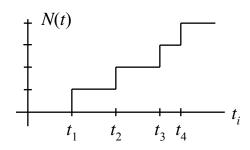
Let N(t) be the number of arrivals in the interval [0, t), i.e., N(t) = N(0,t)

$$\Pr[N(t) = k] = \frac{(\lambda t)^k}{k!} e^{-\lambda t}, \qquad k = 0, 1, 2, \dots$$

• Homogeneous in time: $N(t) = N(0, t) = N(t_1, t_2)$, where $t = t_2 - t_1$



Poisson Process (cont'd.)



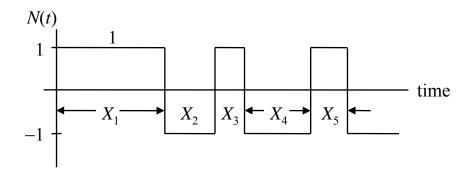
- If $[t_1, t_2]$ and $[t_3, t_4]$ are non-overlapping, $N(t_1, t_2)$ and $N(t_3, t_4)$ are independent.
- For $t_2 > t_1$, $N(t_1, t_2) = N(0, t_2) N(0, t_1)$
- Mean, autocovariance, and autocorrelation functions follow (see text)

$$m_{N}(t) = E[N(t)] = \lambda t$$

$$C_{N}(t_{1}, t_{0}) = E[(N(t_{1}) - m_{N}(t_{1}))(N(t_{0}) - m_{N}(t_{0}))] = \lambda \min(t_{1}, t_{0})$$

$$R_{N}(t_{1}, t_{0}) = C_{N}(t_{1}, t_{0}) + m_{N}(t_{1})m_{N}(t_{0}) = \lambda \min(t_{1}, t_{0}) + \lambda^{2}t_{1}t_{0}$$

Random Telegraph Signal



N(t) changes sign with each arrival of the Poisson process of rate λ

$$Pr[N(0)=1]=p, \quad Pr[N(0)=-1]=1-p$$

$\underline{PMF \text{ of } N(t)}$

$$\Pr[N(t)=1] = \Pr[N(t)=1|N(0)=1] \Pr[N(0)=1]$$

$$+ \Pr[N(t)=1|N(0)=-1] \Pr[N(0)=-1]$$

$$\Pr[N(t)=-1] = \Pr[N(t)=-1|N(0)=1] \Pr[N(0)=1]$$

$$+ \Pr[N(t)=-1|N(0)=-1] \Pr[N(0)=-1]$$

Even number by events:

$$\Pr[N(t) = \pm 1 | N(0) = \pm 1] = \sum_{k=0}^{\infty} \frac{(\lambda t)^{2k}}{(2k)!} e^{-\lambda t} = e^{-\lambda t} \left(\frac{e^{\lambda t} + e^{-\lambda t}}{2}\right) = \frac{1}{2} (1 + e^{-2\lambda t})$$

<u>Odd number of events</u>:

$$\Pr[N(t) = \pm 1 | N(0) = \mp 1] = \sum_{k=0}^{\infty} \frac{(\lambda t)^{2k+1}}{(2k+1)!} e^{-\lambda t} = e^{-\lambda t} \left(\frac{e^{\lambda t} - e^{-\lambda t}}{2}\right) = \frac{1}{2} (1 - e^{-2\lambda t})$$

PMF of N(t) (continued)

We then have

$$\Pr\left[N(t)=1\right] = \frac{1}{2}\left(1+e^{-2\lambda t}\right)p + \frac{1}{2}\left(1-e^{-2\lambda t}\right)\left(1-p\right)$$

$$= \frac{p}{2} + \frac{p}{2}e^{-2\lambda t} + \frac{1}{2} - \frac{p}{2} - \frac{1}{2}e^{-2\lambda t} + \frac{p}{2}e^{-2\lambda t} = \frac{1}{2} + \left(p - \frac{1}{2}\right)e^{-2\lambda t}$$

$$\Pr\left[N(t)=-1\right] = \frac{p}{2}\left(1-e^{-2\lambda t}\right) + \frac{1-p}{2}\left(1+e^{-2\lambda t}\right) = \frac{1}{2} - \left(p - \frac{1}{2}\right)e^{-2\lambda t}$$

Mean, autocorrelation, and autocovariance functions

$$m_{N}(t) = E[N(t)] = (-1)\Pr[N(t) = -1] + (1)\Pr[N(t) = 1]$$

$$= -\frac{1}{2} + \left(p - \frac{1}{2}\right)e^{-2\lambda t} + \frac{1}{2} + \left(p - \frac{1}{2}\right)e^{-2\lambda t} = (2p - 1)e^{-2\lambda t}$$

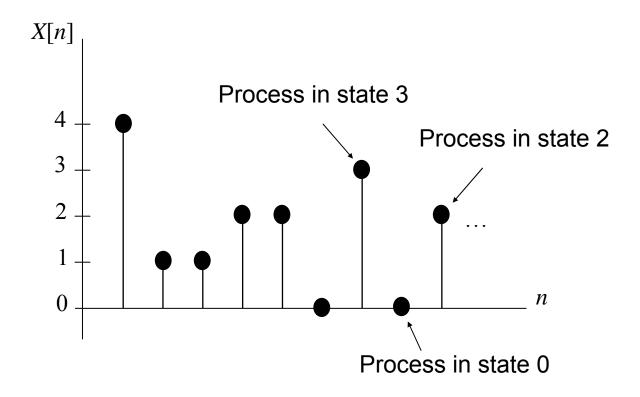
$$R_{N}(t_{1},t_{2}) = E[N(t_{1})N(t_{2})]$$

$$= (+1)\Pr[N(t_{1}) = N(t_{2})] + (-1)\Pr[N(t_{1}) \neq N(t_{2})]$$

$$= \frac{1}{2}[1 + e^{-2\lambda|t_{2}-t_{1}|}] - \frac{1}{2}[1 - e^{-2\lambda|t_{2}-t_{1}|}] = e^{-2\lambda|t_{2}-t_{1}|}$$

$$C_{N}(t_{1},t_{2}) = R_{N}(t_{1},t_{2}) = m_{N}(t_{1})m_{N}(t_{2}) = e^{-2\lambda|t_{2}-t_{1}|} - (2p-1)^{2}e^{-2\lambda(t_{1}+t_{2})}$$

Markov Processes: Discrete-Time Markov Chain



Discrete-Time Markov Chain

Let X[n] be a discrete-time discrete-magnitude random signal. If it satisfies

$$\Pr[X[n] = j | X[n-1] = i_1, X[n-2] = i_2, \dots, X[1] = i_{n-1}, X[0] = i_n]$$

$$= \Pr[X[n] = j | X[n-1] = i_1] \quad \text{for all } n, j, i_1, i_2, \dots, i_n$$

then X[n] is called a discrete-time Markov chain.

State transition probabilities:

for $i = 0, 1, \dots, m-1$

State transition matrix:

$$p_{ij} = \Pr[X[n] = j | X[n-1] = i], \quad p_{00} \quad p_{01} \quad p_{02} \quad \cdots \quad p_{0,m-1} \\ 0 \le i, j \le m-1 \quad \mathbf{P} = \begin{bmatrix} p_{00} & p_{01} & p_{02} & \cdots & p_{0,m-1} \\ p_{10} & p_{11} & p_{12} & \cdots & p_{1,m-1} \\ \vdots & \vdots & \vdots & & \vdots \\ p_{m-1,0} & p_{m-1,1} & p_{m-1,2} & \cdots & p_{m-1,m-1} \end{bmatrix}$$

Rows sum to 1

Example: Consider a 3-state Markov chain

$$\left\{ -1, 0, +1 \right\}$$

state 0 state 1 state 2

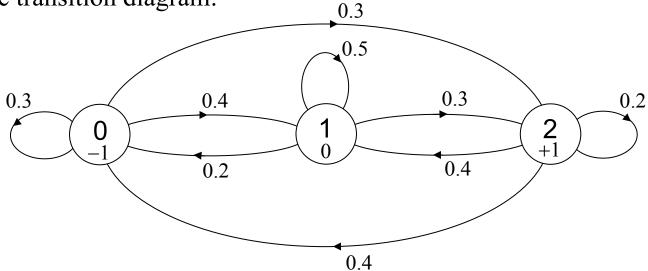
State transition probabilities:

State transition matrix:

$$p_{00} = 0.3$$
 $p_{01} = 0.4$ $p_{10} = 0.2$ $p_{11} = 0.5$ $p_{20} = 0.4$ $p_{21} = 0.4$

$$\mathbf{P} = \begin{bmatrix} 0.3 & 0.4 & 0.3 \\ 0.2 & 0.5 & 0.3 \\ 0.4 & 0.4 & 0.2 \end{bmatrix}$$

State transition diagram:



State Probabilities (not transition probabilities)

The state probability vector at any discrete time k is given by

$$\mathbf{p}[n] = \begin{bmatrix} p_0[n] \\ p_1[n] \\ \vdots \\ p_{m-1}[n] \end{bmatrix} \qquad \sum_{i=0}^{m-1} p_i[n] = 1 \qquad \text{for all } n$$

Then the state vector at time k is given by

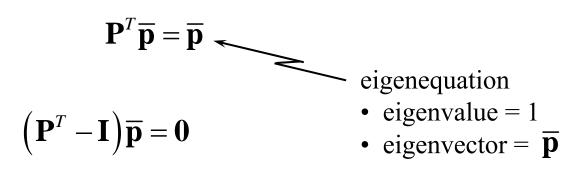
$$\mathbf{p}[n] = \mathbf{P}^T \mathbf{p}[n-1] = (\mathbf{P}^T)^k \mathbf{p}[0], \qquad n = 1, 2, 3, \dots$$

Limiting-State Probabilities

The limiting-state probability vector

$$\overline{\mathbf{p}} = \lim_{n \to \infty} \mathbf{p}[n] = \lim_{n \to \infty} (\mathbf{P}^T)^n \mathbf{p}[0] \quad \Leftarrow \quad \sum_{i=0}^{m-1} \overline{p}_i = 1$$

Assuming that the limiting-state probabilities exist, we have



Solve for $\overline{\mathbf{p}}$ (**P** is known).

Example:

$$\mathbf{P} = \begin{bmatrix} 0.6 & 0.4 \\ 0.1 & 0.9 \end{bmatrix}, \qquad \sum_{i=0}^{1} \overline{p}_i = 1$$

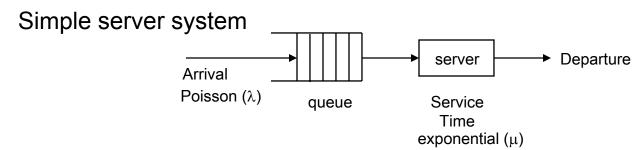
(a) Find $\overline{\mathbf{p}}$.

$$\begin{aligned} \left(\mathbf{P}^{T} - \mathbf{I}\right) \overline{\mathbf{p}} &= \underline{0} \implies \begin{bmatrix} -0.4 & 0.1 \\ 0.4 & -0.1 \end{bmatrix} \begin{bmatrix} \overline{p}_{0} \\ \overline{p}_{1} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\ \frac{4\overline{p}_{0}}{\overline{p}_{0}} &= \overline{p}_{1} \\ \overline{p}_{0} &+ \overline{p}_{1} &= 1 \end{aligned} \implies \begin{aligned} \overline{p}_{0} &= 0.2 \\ \overline{p}_{1} &= 0.8 \end{aligned}$$

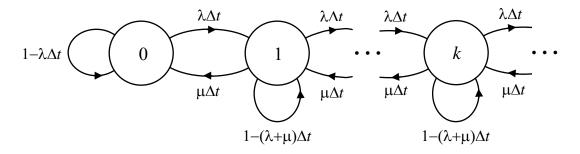
(b) Find the probability of a run of ten values of state 0

$$(0.2)(0.6)^9 = 0.002$$

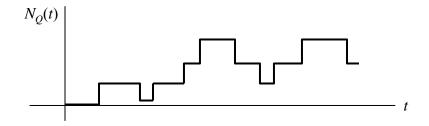
Continuous-Time Markov Chain



The queue can be described by a <u>continuous-time Markov chain</u> with a possibly *infinite* number of states.

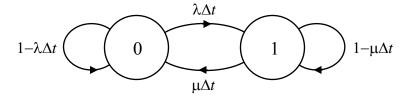


The Markov random process looks like:

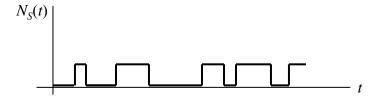


Continuous-Time Markov Chain (cont'd.)

The <u>server</u> can be described by a <u>continuous-time Markov chain</u> with just two states.



The Markov random process looks like:



Transition Rate Diagram

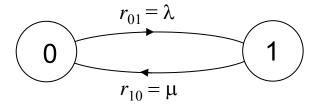
Let N(t) be a continuous-time Markov chain.

Transition Rates

 r_{ij} are rates of the Poisson process defining transitions from state i to state j.

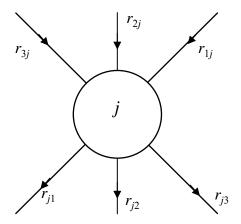
A <u>transition rate diagram</u> is a state diagram with the rates indicated. Note that the rates do not represent probabilities directly and there are no self-loops.

Example for the service process:



Time-Dependent State Probabilities

Now consider a more general Markov chain. A typical state has multiple transitions to and from other states:



Define $p_j(t) = \Pr[N(t) = j]$. Then,

$$p_{j}\left(t+\Delta t\right) = \sum_{\substack{\ell=0\\\ell\neq j}}^{m-1} r_{\ell j} \Delta t \cdot p_{\ell}\left(t\right) + \left(1 - \sum_{\substack{\ell=0\\\ell\neq j}}^{m-1} r_{j\ell} \Delta t\right) p_{j}\left(t\right)$$

Time-Dependent State Probabilities (cont'd.)

$$p_{j}\left(t+\Delta t\right) = \sum_{\substack{\ell=0\\\ell\neq j}}^{m-1} r_{\ell j} \Delta t \cdot p_{\ell}\left(t\right) + \left(1 - \sum_{\substack{\ell=0\\\ell\neq j}}^{m-1} r_{j\ell} \Delta t\right) p_{j}\left(t\right)$$

Rearranging:

$$\frac{p_{j}\left(t+\Delta t\right)-p_{j}\left(t\right)}{\Delta t}=\sum_{\substack{\ell=0\\\ell\neq j}}^{m-1}r_{\ell j}\;p_{\ell}\left(t\right)-\left(\sum_{\substack{\ell=0\\\ell\neq j}}^{m-1}r_{j\ell}\right)p_{j}\left(t\right)$$

In the limit:

$$\frac{dp_{j}(t)}{dt} = \sum_{\ell=0}^{m-1} r_{\ell j} p_{\ell}(t) \quad \text{where} \quad r_{jj} = -\sum_{\substack{\ell=0 \ \ell \neq j}}^{m-1} r_{j\ell}$$

(Chapman-Kolmogorov equation for continuous-time Markov chains)

Global Balance Equations

Beginning with the Chapman-Kolmogorov equation:

$$\frac{dp_{j}(t)}{dt} = \sum_{\ell=0}^{m-1} r_{\ell j} p_{\ell}(t) \qquad j = 0, 1, \dots, m-1$$

For steady-state probability flow-rate balance, let:

$$t \to \infty \implies p_{j}(t) \to p_{j} \implies \frac{dp_{j}(t)}{dt} \to 0$$

$$\therefore \sum_{\ell=0}^{m-1} r_{\ell j} p_{\ell} = 0 \qquad j = 0, 1, \dots, m-1$$

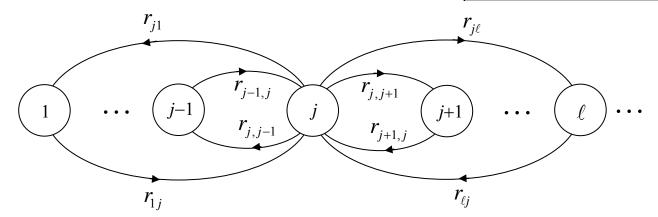
Global Balance Equations (cont'd.)

$$\sum_{\ell=0}^{m-1} r_{\ell j} \ p_{\ell} = 0 \qquad j = 0, 1, \dots, m-1$$

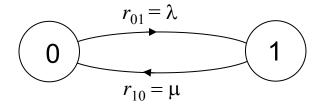
Now recall that,
$$r_{jj} = -\sum_{\substack{\ell=0 \ \ell \neq j}}^{m-1} r_{j\ell}$$
 Thus $\sum_{\substack{\ell=0 \ \ell \neq j}}^{m-1} r_{\ell j} \; p_{\ell} - p_{j} \sum_{\substack{\ell=0 \ \ell \neq j}}^{m-1} r_{j\ell} = 0$

Probability flow-rate balance equation:

$$p_j \sum_{\substack{\ell=0\\\ell\neq j}}^{m-1} r_{j\ell} = \sum_{\substack{\ell=0\\\ell\neq j}}^{m-1} r_{\ell j} \ p_\ell$$



Example:



For State 0: $\lambda p_0 = \mu p_1$

(Global balance equations)

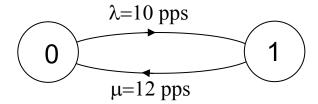
For State 1: $\mu p_1 = \lambda p_0$

Also use: $p_0 + p_1 = 1$

to find:

$$p_0 = \frac{\mu}{\lambda + \mu}; \qquad p_1 = \frac{\lambda}{\lambda + \mu}$$

Numerical Example:

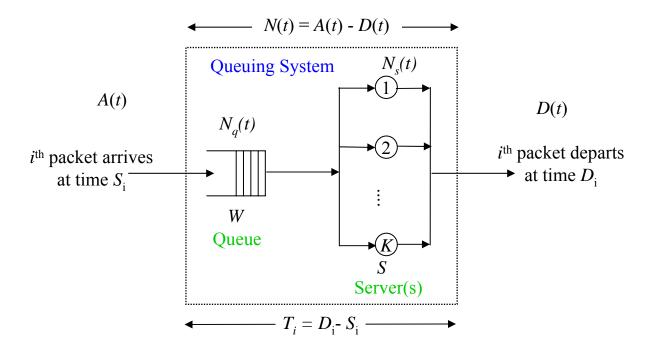


$$\lambda p_0 = \mu p_1 \implies p_1 = \frac{\lambda}{\mu} p_0 = \frac{5}{6} p_0$$

$$p_0 + p_1 = 1 \implies p_0 + \frac{5}{6} p_0 = 1$$

$$p_0 = \frac{6}{11}, \quad p_1 = \frac{5}{11}$$

Queuing System: M/M/K†



N(t): Number of packets in system

T: Time spent in system

 $N_q(t)$: Number of packets in queue

W: Waiting time in queue

 $N_s(t)$: Number of packets in service S: Service time

† Shorthand notation: a/b/c/d

Arrival process/Service time distribution/Number of servers/Buffer size

Single Server Queuing System: M/M/1 System

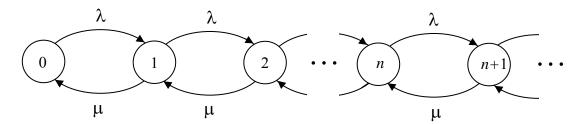
• Job arrival is a Poisson process and the interarrival time τ is exponentially distributed with λ as the parameter

$$\Pr[A(t) = n] = \frac{(\lambda t)^n}{n!} e^{-\lambda t}, \quad n = 0, 1, 2, \dots$$
$$f_{\tau}(\tau) = \lambda e^{-\lambda \tau}, \quad \tau \ge 0$$

• Job service time S is exponentially distributed with μ as the parameter

$$f_S(s) = \mu e^{-\mu s}, \quad s \ge 0$$

Assume an infinitely long queue (birth-death queue)



with state transition rates: $r_{i, i+1} = \lambda$, $r_{i, i-1} = \mu$, $j = 0, 1, 2, \cdots$

$$r_{i, i-1} = \mu_i$$

$$j = 0, 1, 2, \cdots$$

Global Balance Equations (by observation)

State 0:
$$\lambda p_0 = \mu p_1$$

State 0:
$$\lambda p_0 = \mu p_1$$
 $\lambda p_0 - \mu p_1 = 0$
State 1: $(\lambda + \mu) p_1 = \lambda p_0 + \mu p_2$ $\lambda p_1 - \mu p_2 = \lambda p_0 - \mu p_1 = 0$
... $\lambda p_0 - \mu p_1 = 0$
State 1: $(\lambda + \mu) p_1 = \lambda p_0 + \mu p_2$ $\lambda p_1 - \mu p_2 = \lambda p_0 - \mu p_1 = 0$
State n: $(\lambda + \mu) p_n = \lambda p_{n-1} + \mu p_{n+1}$ $\lambda p_n - \mu p_{n+1} = \lambda p_{n-1} - \mu p_n = 0$

State *n*:
$$(\lambda + \mu) p_n = \lambda p_{n-1} + \mu p_{n+1}$$

$$\lambda p_0 - \mu p_1 = 0$$

$$\lambda p_1 - \mu p_2 = \lambda p_0 - \mu p_1 = 0$$

$$\lambda p_n - \mu p_{n+1} = \lambda p_{n-1} - \mu p_n = 0$$

Global balance equations

$$\lambda p_0 - \mu p_1 = 0$$

$$\lambda p_1 - \mu p_2 = 0$$

$$\lambda p_n - \mu p_{n+1} = 0$$
 or $p_j = \frac{\lambda}{\mu} p_{j-1}$ $j = 1, 2, 3, \dots, n, n+1, \dots$

By induction, the state probabilities:

$$p_n = \left(\frac{\lambda}{\mu}\right)^n p_0; \qquad n = 0, 1, 2, 3, \cdots$$

Rewrite:
$$p_n = \rho^n p_0$$
; $n = 0, 1, 2, 3, \dots$ where $\rho = \frac{\lambda}{\mu}$

This defines a PMF for the state of the queue

$$f_{N}[n] = \Pr[N = n] = p_{n}$$

$$\begin{bmatrix} p_{0} & p_{1} & p_{2} & p_{3} & p_{4} & p_{j} & p_{4} & p_{j} & p_{k} & p_{k$$

$$f_{N}[n] = \Pr[N = n] = p_{n}$$

$$\begin{bmatrix} p_{0} & p_{1} & p_{2} & p_{3} & p_{4} & p_{j} & p_{4} & p_{j} & p_{k} & p_{k$$

To determine the unknown p_0 use:

$$\sum_{j=0}^{\infty} p_j = \sum_{j=0}^{\infty} \rho^j p_0 \qquad p_0 \sum_{j=0}^{\infty} \rho^j = p_0 \frac{1}{1 - \rho} = 1$$

for $\rho < 1$, i.e., $\lambda < \mu$, thus $p_0 = 1 - \rho$ and

$$f_N[n] = p_n = (1-\rho)\rho^n, \quad n = 0,1,2,\cdots$$

Thus N, which represents the number of jobs in the system, is a type 0 geometric random variable. ρ is called the <u>utilization factor</u> $(0 < \rho < 1)$.

Some Important Formulas

1. <u>Probability of long queues</u>:

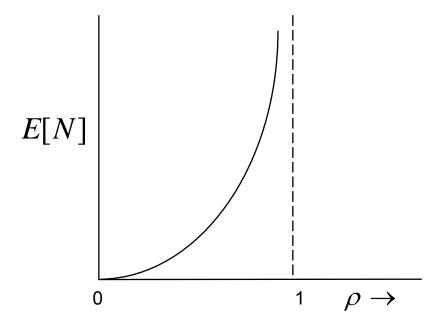
$$\Pr[N < n_0] = \sum_{j=0}^{n_0 - 1} (1 - \rho) \rho^j = (1 - \rho) \sum_{j=0}^{n_0 - 1} \rho^j$$
$$= (1 - \rho) \cdot \frac{1 - \rho^{n_0}}{1 - \rho} = 1 - \rho^{n_0}$$
$$\Pr[N \ge n_0] = \rho^{n_0}$$

Important Formulas (cont'd.)

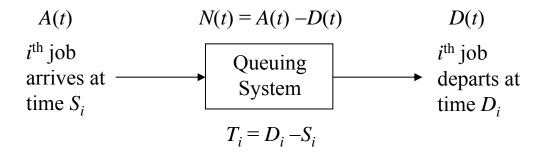
2. Average number of jobs in the system:

$$E[N(t)] = \frac{\rho}{1-\rho}$$

(mean of the geometric PMF)



Little's Formula



For systems that reach equilibrium, the average number of jobs *N* in a system is

$$E[N(t)] = \lambda E[T]$$

where E[T] is the average time spent in the system by a job.

Comments on Little's Formula

Little's formula can be extended to other quantities. Let T = W + S where W is the waiting time in the queue and S is the service time (note that $E[S] = 1/\mu$).

• The average number of jobs in the queue is given by

$$E\left[N_q(t)\right] = \lambda E[W] \tag{1}$$

• The average number of jobs in service or utilization of a single server system is

$$E[N_S(t)] = \lambda E[S] = \lambda / \mu = \rho \tag{2}$$

where E[S] is the average service time.

• The utilization of a K-server system is then given by

$$\rho_K = \frac{\lambda E[S]}{K} = \frac{\lambda}{K\mu}$$

Comments (cont'd.)

• The average total delay experienced by a job in a single server system

$$E[T] = \frac{E[N(t)]}{\lambda} \quad \leftarrow \text{ from little's formula}$$

$$= \frac{1}{\lambda} \cdot \frac{\rho}{1 - \rho} = \frac{1}{\lambda} \cdot \frac{\lambda/\mu}{1 - \lambda/\mu} \quad \leftarrow \text{ Note } \rho = \frac{\lambda}{\mu}$$

$$E[T] = \frac{1}{\mu - \lambda}$$
(3)

Comments (cont'd.)

• The average waiting time in the queue

$$E[W] = E[T] - E[S] = \frac{\rho}{\lambda(1-\rho)} - \frac{\rho}{\lambda} = \frac{\rho^2}{\lambda(1-\rho)}$$
(4)

• The average number of jobs in the queue

$$E[N_q] = \lambda E[W] \qquad \leftarrow \text{Little's formula restated}$$

$$= \frac{\rho^2}{1 - \rho} \tag{5}$$

Example:

Consider an M/M/1 system

(a) Find Pr [N(t) > 10]

$$\Pr[N(t) > 10] = \Pr[N(t) \ge 11] = \rho^{11}$$

(b) Find the maximum allowable arrival rate, λ , if we require $\Pr[N(t) \ge 10] = 10^{-3}$. Let $\mu = 4$ per second

$$\Pr[N(t) \ge 10] = \rho^{10} = 10^{-3}$$

$$\therefore \quad \rho = \frac{\lambda}{\mu} = 10^{-0.3}$$

$$\lambda = \mu 10^{-0.3} \cong 2$$

Example (cont'd.):

(c) Find the minimum allowable service rate, μ , if we require $\Pr[N(t) \ge 10] = 10^{-5}$. Let $\lambda = 4$ per second

$$\Pr[N(t) \ge 10] = \rho^{10} = 10^{-5}$$

$$\therefore \quad \rho = \frac{\lambda}{\mu} = 10^{-0.5}$$

$$\mu = \frac{\lambda}{10^{-0.5}} \cong 13$$

Example: M/M/1 system

Packets arrive at a network router at a rate $\lambda = 2 \times 10^5$ per sec.

The service is performed by the router at a rate $\mu = 2.5 \times 10^5$ per sec.

The utilization factor,
$$\rho = \frac{\lambda}{\mu} = \frac{2}{2.5} = \frac{4}{5}$$

PMF,
$$f_N[n] = (1-\rho)\rho^n, n \ge 0.$$

(a) Find the mean number of jobs in the system, E[N(t)].

$$E[N(t)] = \frac{\rho}{1-\rho} = \frac{0.8}{1-0.8} = 4$$

Example (cont'd.):

(b) Average total delay in the system. From Little's formula

$$E[T] = \frac{E[N(t)]}{\lambda} = \frac{4}{2 \times 10^5} = 20 \,\mu\text{s}$$

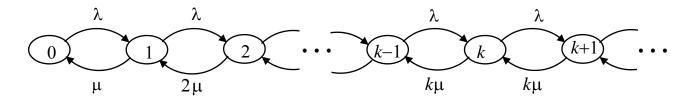
(c) What value of λ would double E[T] in (b)?

$$E[T] = \frac{1}{\mu - \lambda} = 40 \,\mu\text{s or } \mu - \lambda = \frac{10^6}{40} = 0.25 \times 10^5$$
$$\lambda = \mu - 0.25 \times 10^5 = 2.5 \times 10^5 - 0.25 \times 10^5 = 2.25 \times 10^5 \text{ per sec}$$

(d) What is the utilization? (0.9)

M/M/k System

The state transition diagram for an M/M/k system



The state probabilities of this queue can be written as

$$p_{n} = \frac{\lambda}{n\mu} p_{n-1} = \frac{1}{n!} \left(\frac{\lambda}{\mu}\right)^{n} p_{0}, \quad n = 1, 2, \dots, k$$

$$p_{n} = \frac{\lambda}{k\mu} p_{n-1} = \left(\frac{\lambda}{k\mu}\right)^{n-k} p_{n} = \rho^{n-k} p_{k}, \quad n = k+1, k+2, \dots$$

where ρ is defined as $\rho = \lambda/k\mu$.

By substituting for p_k , we have

$$p_n = \frac{1}{k!} \left(\frac{\lambda}{\mu}\right)^k \rho^{n-k} p_0, \quad n = k+1, \ k+2, \ k+3, \cdots$$

The probability of the 0th state is obtained as follows:

$$\sum_{n=0}^{\infty} p_n = 1 = p_0 + p_0 \sum_{n=1}^{k-1} \frac{1}{n!} \left(\frac{\lambda}{\mu}\right)^n + p_0 \sum_{n=k}^{\infty} \frac{1}{k!} \left(\frac{\lambda}{\mu}\right)^k \rho^{n-k}$$

$$p_0 = \left[\sum_{n=0}^{k-1} \frac{1}{n!} \left(\frac{\lambda}{\mu}\right)^n + \frac{1}{k!} \left(\frac{\lambda}{\mu}\right)^k \frac{1}{1-\rho}\right]^{-1}$$

The probability that an arriving job is forced to wait because all *k*-servers are busy is known as the Erlang C formula:

$$C\left(k, \frac{\lambda}{\mu}\right) = \Pr[W > 0] = \Pr[N > k] = \sum_{n=k}^{\infty} p_n$$
$$= \sum_{n=k}^{\infty} \rho^{n-k} p_k = \frac{p_k}{1-\rho}$$

The average number of customers in the queue is given by

$$E[N_q] = \sum_{n=k}^{\infty} (n-k) \rho^{n-k} p_k = p_k \sum_{i=0}^{\infty} i \rho^i = \frac{\rho}{(1-\rho)^2} p_k$$

From Little's formula:
$$E[W] = \frac{E[N_q]}{\lambda} = \frac{\rho}{\lambda(1-\rho)^2} p_k$$

The system delay is then given by:

$$E[T] = E[W] + E[S] = \frac{\rho}{\lambda (1-\rho)^2} p_k + \frac{1}{\mu}$$
$$= \frac{1}{k!} \frac{\rho}{\lambda (1-\rho)^2} \left(\frac{\lambda}{\mu}\right)^k p_0 + \frac{1}{\mu}$$

By using Little's formula, the total jobs in the system can then be obtained as

$$E[N] = \lambda E[T]$$

Continuous-time Markov chain

- M/M/1 queue

$$E[N(t)] = \frac{\rho}{1-\rho} \qquad E[N(t)] = \lambda E[T] \qquad \rho = \frac{\lambda}{\mu}$$

$$E[N(t)] = \lambda E[T]$$

$$\rho = \frac{\lambda}{\mu}$$

- M/M/k queue

$$E[T] = \frac{1}{k!} \frac{\rho}{\lambda (1-\rho)^2} \left(\frac{\lambda}{\mu}\right)^k p_0 + \frac{1}{\mu}$$

$$\rho = \frac{\lambda}{k\mu}$$

Example:

Compare queuing systems:

A. M/M/1 system with one 100 GIPS server

$$\lambda = 5000$$
 per sec, $\mu = 6000$ per sec

$$E[T] = \frac{1}{\mu - \lambda} = \frac{1}{6000 - 5000} = 1 \text{ ms}$$

B. Ten M/M/1 systems each with a 10 GIPS server

with $\lambda = 500$ per sec, $\mu = 600$ per sec

$$E[T] = \frac{1}{\mu - \lambda} = \frac{1}{600 - 500} = 10 \text{ ms}$$

The mean delay in the 100 GIPS system is 1/10th that of the system with ten 10 GIPS servers.

Example (cont'd.):

C. An M/M/10 system with a 10 GIPS server:

$$E[T] = \frac{1}{k!} \frac{\rho}{\lambda (1 - \rho)^2} \left(\frac{\lambda}{\mu}\right)^k p_0 + \frac{1}{\mu}$$
$$= 8.8278 \times 10^{-12} p_0 + \frac{1}{\mu} \cong \frac{1}{\mu}$$
$$= \frac{1}{600} = 1.6667 \text{ ms}$$